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A five-step drone collaborative planning approach for the management of distributed spatial events and vehicle notification using multi-agent systems and firefly algorithms

Hana Gharrad [a], Nafaa Jabeur [b,*], Ansar Ul-Haque Yasar [a], Stephane Galland [c], Mohammed Mbarki [d]

[a] Transportation Research Institute (IMOB), Hasselt University, Hasselt, Belgium
[b] German University of Technology in Oman (GUtech), Athaibah, Sultanate of Oman
[c] CIAD, Univ. Bourgogne Franche-Comté, UTBM, F-90010 Belfort, France
[d] MARS Research Laboratory, LR 17ES05, Sousse University, Technopole of Sousse, 4054, Sousse, Tunisia

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ABSTRACT

In spite of the performance that existing approaches for drone collaborative planning have demonstrated, there is still a need for new solutions which are capable of effectively identifying the right tasks for the right drones at the right times while maximizing the total benefits obtained from the drones' actions. These new solutions should be particularly tested within the context of intelligent transportation systems to assess their impact on mobility and traffic flow. In order to address these issues, we present in this paper a new a five-step solution for drone collaborative planning. Our solution uses a Multi-Agent System as well as a Firefly Algorithm solution to enable drones jointly neutralize ongoing events by considering trust factors and cost/benefit analysis. The solution, which is also capable of issuing appropriate warnings to vehicles to prevent them from incurring any undesirable/dangerous impact due to ongoing events, is using a reward-driven competition to encourage drones to join collaborating teams. Our simulations are showing promising results in terms of processing time, energy consumption, and total reward obtained compared to two other planning approaches relaying on random and priority-based selection of the next locations that drones will visit respectively.

1. Introduction

We are recently witnessing an increasing attention to the use of drones in a wide range of application domains, including precision farming, military operations, transportation, and infrastructure inspection. This attention is particularly motivated by the continuous technological progress that is endowing drones with better capabilities for data acquisition, onboard processing, and communication. As these capabilities are not yet enough to adequately manage complex events as well as handling increasing amounts of data, recent works (e.g., [1, 2, 3]) have proposed collaboration approaches to boost drone's actions toward achieving goals beyond individual abilities. In this regard, several solutions have addressed joint patrolling and tracking operations (e.g., [4, 5]), collaborative surveillance (e.g., [6]), and collaborative rescue missions (e.g., [7, 8]). Other approaches have focused on collaborative planning, which is defined as a refinement process whereby current plans could be modified by cooperating entities driven by their individual intensions [9]. Several issues have been addressed within this context, including obstacle avoidance (e.g., [10, 11], and [12]), path overlap avoidance (e.g., [3, 2]), and scheduling trajectories (e.g., [13]). To collaboratively create harmony within a swarm of drones and perform the expected tasks according to specific criteria (e.g., time, energy constraints, quality of service, etc.), numerous works have relayed on the use of artificial intelligence solutions, including Multi-Agent Systems (e.g., [8, 7, 14, 6, 15]), Particle Swarm Optimization - PSO (e.g., ([16]), Self-Organizing Map - SOM (e.g., [17]), [18]), and Bacteria Foraging - BF (e.g., [19]). The proposed solutions, which have not addressed the specific field of intelligent transportation, have demonstrated remarkable improvements on the performance of collaborating drones. Nevertheless, we argue that new approaches are still needed to better allow drones decide on their own when and where to collaborate and with whom. Within this context, we are proposing a new

* Corresponding author.
E-mail address: nafaa.jabeur@gutech.edu.om (N. Jabeur).

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solution based on the Multi-Agent System (MAS) paradigm and driven by a bio-inspired Firefly Algorithm (FA) to implement drone collaborative planning and solve ongoing events of interest. In addition to optimizing the operations of drones, our solution is also aiming to generate the right warnings to vehicles approaching areas with active events so they can avoid potentially dangerous driving situations and prevent any impact on road traffic flow. We summarize our contributions in this paper as follows: (1) A five-step approach for drone collaborative planning based on a MAS approach (2) A FA-based solution that enables drones to collaboratively neutralize ongoing events by considering trust factors and cost/benefit analysis; and (3) An intelligent approach whereby drones carry out a reward-driven competition to join collaborating teams and generate the right warnings to vehicles ongoing events' locations.

In the reminder of this paper, Section 2 highlights the related works on drone collaboration. Section 3 sheds lights on our proposed five-step solution called ASBAF, where we explain the mechanisms used by autonomous drones to assess ongoing situations, set up the collaboration framework, bid for collaboration contributions, agree on joint action plan, and provide feedbacks to collaborating drones. The section also gives details on our proposed MAS and FA bio-inspired solution. Section 4 outlines our implementation results and performance analysis.

2. Related work

Collaboration has been proposed as a promising alternative to enable groups of drones handle complex events, particularly in large environments requiring extended flight times and a thorough tracking of dynamic objects/events. In this regard, [4] have deployed drones for a collaborative patrolling and cleaning mission in an expandable contaminated area. The environment is modelled as an undirected graph that describes a two-dimensional integer grid, where each drone has to decide the tiles to be visited based on the actions of other drones, the potential of the tiles, and a transition matrix. In [5], drones have been used for a continuous cooperative tracking based on a dedicated formation control method. The method models the configurations of leader/follower drones and uses a potential function to determine their paths during tracking missions. In [6], the authors have used collaborative drones to survey a disaster site and ultimately help rescue teams in planning their actions. In order to collaborate, the drones use a reactive/intelligent assignment whereby the number of drones and their tasks are initially determined by analyzing the current data about the disaster site. The number of drones could then increase based on the number of distress messages broadcasted by the victims. Drones, which can each handle a predefined number of distress messages, use individual blackboards to share relevant information about their missions. In [7], drones have been used for search and rescue applications. The authors have suggested to create join plans by means of a negotiation process. In each step of this process, one drone will optimize its actions according to the current plans of the other drones while considering the interdependencies between the different tasks to be executed. This approach was extended in [8], where the authors have proposed a dedicated planner that adjusts the plans of the collaborating drones to optimize their behaviors.

Drone collaboration have addressed several issues, including planning. Planning refers to the process of task decomposition and task allocation [1]. It can also be seen as a deliberation process that organizes actions by anticipating their outcomes [20]. Collaborative planning can be defined as a refinement process whereby current plans may be modified by cooperating entities driven by their individual intensions [9]. Within the specific context of drones, collaborative path planning refers to the scheduling of the trajectories of several drones while considering their synergistic constraints and ultimately allowing them to work together at a minimum cost [13]. Among the several works that have addressed this issue, we can highlight the approaches proposed by [10, 11], and [12] where drones are deployed to avoid obstacles and jointly cover a given inspection area. During their joint actions, drones are particularly aiming to reduce their energy consumptions and operation times. In [2], a reinforcement learning-based trajectory planning approach has been used to plan the actions of drones in the context of search and tracking application. The approach uses a quantum probability model for the predication of targets' positions. Drones can then collaboratively plan their trajectories based on the output of a partner movement prediction model. In [3], the authors have used free learning techniques to enable patrolling drones to fully cover an unknown field while minimizing overlaps between their paths. In this work, drones use a game-theoretic Correlated Equilibrium (CE) approach to reach a consensus on the selection of actions and, consequently, the creation of individual paths. In this approach, social convention rules are used to assign ranks to drones. Based on these ranks, priorities are determined during the establishment of trajectories. In [21], the authors have proposed an approach for fully autonomous multi-cooperative drone system for intruder detection and isolation. The authors have represented the problem as a deterministic pursuit and evasion game where drones coordinate their actions and define their paths by exchanging messages about their current states as well as the state of the environment.

Because of the current processing, communication, and flight-time constraints, drones are not yet capable of establishing effective collaborations and jointly planning their trajectories. This is particularly due to the lack of their intelligence and autonomy in deciding on the tasks they will execute with respect to their own constraints, commitments, and capabilities. To overcome these shortcomings, recent solutions have used MAS paradigm, which was successfully deployed in a large number of research works (e.g., [22, 23, 24, 25]) to enable distributed, autonomous peers achieve common goals exceeding their individual capabilities. The success of MAS is mainly attributed to its significant performance in performing missions where human-like intelligence is essential to advance the autonomy of peers in discovering, interpreting, and exchanging new knowledge, timely supporting changing constraints within dynamic and unpredictable environments, and planning the right actions accordingly. In the particular field of drones, Zargar et al. [26] have benefited from the social behaviors of agents and their proven capabilities in mimicking human strategies to implement a new collaborative approach between drones. In the proposed approach, where each drone is represented with an agent, the spatial environment is divided into several zones (also islands). A balance function is then used to enable a periodic exchange of information between agents (representing here both the drones and the islands). Although the authors have mentioned that this information is used to create trajectories via drone collaboration, no explicit details are given. Samad et al. [6] have deployed software agents to allow drones to autonomously collaborate in the aftermath of a disaster. Using their context-awareness and communication capabilities as well as a blackboard consolidation approach, agents are deployed to implement effective decision-making and smart planning processes. Each drone must visit a set of locations received from victims. The information collected by the drones from their survey zones is published in the blackboard, which is accessible to all agents. The blackboard information also includes the evaluation of the damage extents in affected areas. This information is used to assign the right number of drones to any given area. In [15], the authors have used MAS with a reinforcement learning approach to model a swarm of drones and allow them to collaboratively act while remaining within mutual communication ranges. In the proposed solution, every drone identifies its own path from the motions of the other collaborating drones.

In addition to MAS, some research works have proposed bio-inspired approaches for drone collaborative planning. In this regard, Odonkor et al. [16] have used Particle Swarm Optimization (PSO) to allow drones to collaboratively track oil spill with frugal sharing knowledge. In this approach, drones start with a scouting phase where they generate their waypoints based on clustered oil locations. They then collaboratively create an oil spill map based on which they identify the promising

Table 1
System model.

Element	Set	Description
Drones	$D = \{d_i, i = 1, \ldots, n\}$	Set of n drones. Every drone d_i has a location (xd_i, yd_i)
Area	$A = \{z_i, i = 1, \ldots, m\}$	The deployment area A is divided into m zone. Every zone z_i will be divided into several tiles
Ground Controllers	$G = \{g_i, i = 1, \ldots, p\}$	Every ground controller g_i has a location (xg_i, yg_i). The parameter p represents the number of ground controllers
Charging Stations	$C = \{c_i, i = 1, \ldots, h\}$	Two types of charging stations may be available: static and mobile. Every charging station c_i has a location (xc_i, yc_i). The parameter h represents the number of charging stations.
Resources	$R = D \cup G \cup C = \{R_i, i = 1, \ldots, v\}$	Every resource r_i has a location (xr_i, yr_i). The parameter v represents the number of resources. In a given zone z_i, the available resources are $R_i = \{r_i, i = 1, \ldots, u \mid (xr_i, yr_i) \in z_i$, where u represents the number of resources in $z_i\}$
Warnings	$W = \{w_i, i = 1, \ldots, s_{max}\}$	Every warning type w_i will reflect the current situation in a given zone. The parameter s represents the number of warnings

Table 2
Simulation parameters.

Metric	Value
Drone Max Battery Capacity Voltage	20v
Drone Max Flight time	400 cycles
Average Amp Draw	40 Amps
Size of the Field of view	$148.42 m^2$
Required Flight time to go to charging station	10 cycle
Charging time	500 cycle
Communication Range	135.2 m
Size of the area	6.51 km * 5.14 km
Size of the tile	434.4 m * 342.8 m
Number of drones	9 drones
Number of simulations	30 simulations
Cycle	1 s
γ (coefficient of brightness fading)	0.5
A (cell priority factor)	1
φ_0 (drone initial reputation)	0.5
$\mathbf{q}(t)$ (number of charging stations available in a given cell at time t)	1

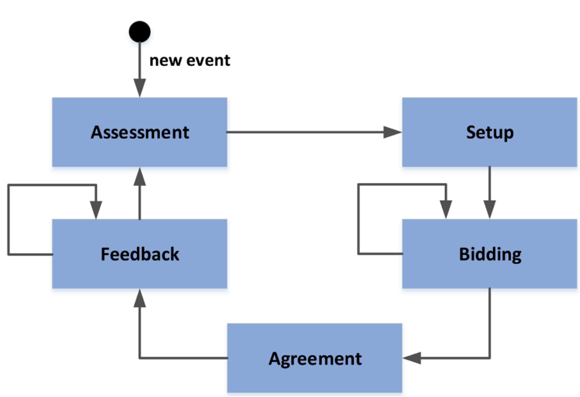

Fig. 1. The proposed five-step ASBAF approach.

unexplored areas in their vicinities and move to the ones with higher local influences to expand their spatial explorations. To update the planning of their paths while minimizing trajectory overlaps, drones frequently share updates concerning an occupancy grid. In [17], the authors have proposed an approach for task allocation and path planning for underwater drones. The approach uses a Self-Organizing Map (SOM) to assign targets to drones. In order to find the shortest collision-free paths to targets, drones use a Glasius Bio-inspired Neural Network (GBNN) solution. This solution was extended in [18] to support the identification of dynamic underwater obstacles. In [19] the authors have suggested a MAS approach inspired from Bacteria Foraging (BF) to allow drones to explore an unknown area and find a moving target. To this end, they have allowed the software agents (representing here the drones) to explore the environment without any predefined pattern. Instead, they explore the most viable spatial locations by following attraction and repulsion forces relative to their waypoints.

Based on our literature review, we argue that the use of artificial intelligence approaches for drone collaborative planning has demonstrated promising results. Nevertheless, we also argue that planning, which also includes environment discovery, task allocation, dynamic team formation, and path planning, still requires better intelligent mechanisms to identify collectively and effectively the right tasks for the right drones and coordinate their executions toward an optimized use of the restricted available resources and during acceptable timeframes. We are aiming in this paper to address these shortcomings. In contrast with the existing literature, we are going to focus on the particular context of intelligent transportation systems, where the solution should demonstrate a positive impact on road traffic flow.

3. A new bio-inspired intelligent drone collaborative planning approach

3.1. System model

Our main aim in this paper is to allow drones to jointly plan and optimize their activities for the management of ongoing events of interest. To this end, we consider a model consisting in n drones having the same initial capabilities. We assume that each drone has its own mission; that is to inspect a given geographic area according to a predefined path (e.g., circular path, zigzag path, the path following a road, spiral pattern, Zamboni pattern, etc.). Based on new events detected, the drone may adapt its mission as well as its path accordingly. We assume that drones are deployed in an area A. The area A is divided into m zones z_i, $i = 1, \ldots, m$. In each zone z_i, we have a set of resources r_i, including the available drones, one or more charging stations, and a ground controller g_i (Table 1). We assume that every drone is equipped with a GPS for localization purposes as well as with the necessary sensors to detect the events, which are important to their envisioned use. Furthermore, we assume that drones can communicate with their neighbors located within their communication ranges, they have the necessary knowledge about the spatial areas along their trajectories, they are equipped with sensors to avoid obstacles and collisions, they know the locations of the charging stations, and their operation schedules are accessible. Moreover, we assume that drones can detect and exchange with ground vehicles within their communication ranges by sending to them several types of warnings. These warnings are based on the vehicles' locations and their expected destinations. They are also based on the current intensity/impact of the event in these destinations.

3.2. The five-step ASBF collaboration approach

We propose in this paper a five-step approach called ASBAF (Fig. 1) for drone collaboration planning. The proposed steps are as follows: (1) Assessment (assessing the event scope and its related risks); (2) Setup (identifying and sharing ongoing events' parameters with potential collaborating peers); (3) Bidding (competing to contribute to the collaborative planning); (4) Agreement (negotiating a joint plan based on collaborating drones' preferences); and (5) Feedback (monitoring the event and generating the warnings to vehicles on the ground while adapting the collaboration plans and actions accordingly).

As some actions in our ASBAF approach need relatively extended

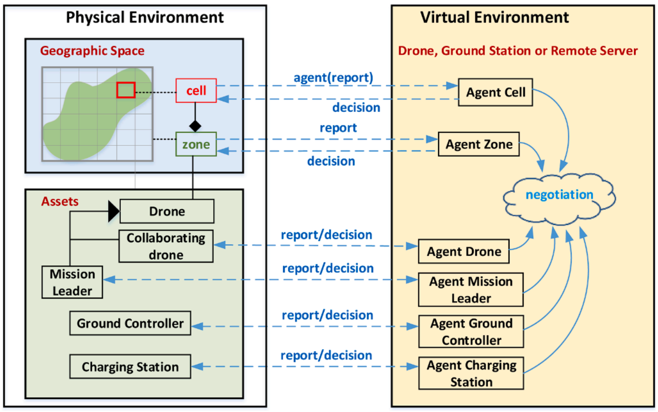

Fig. 2. Our proposed MAS architecture.

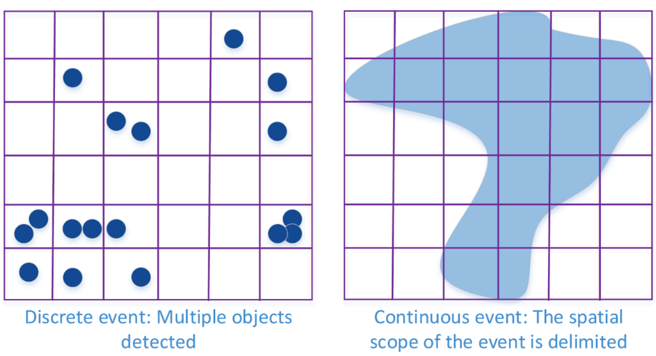

Fig. 3. Types of events: (left) Discrete (e.g., intruders); (right) Continuous (e.g., wildfire).

processing capabilities, and also because of the intrinsic distributed nature of the system, we propose to use a MAS-based solution to support and optimize drones' operations. The architecture of our MAS (Fig. 2) includes two environments: The physical environment (which consists in the geographic space where the events of interest are happening as well as the assets, including the drones, the charging stations, and the ground stations) and the virtual environment (which represents the location where the actions of drones will be negotiated and the joint plan will be established. This location could be the drone itself, a ground station, or a remote server). For more details, the next sections will shed light on how several software agents will migrate to the virtual environment and negotiate the right actions to execute on behalf of the assets they represent.

In order to motivate drones to collaborate and contribute to the management of the ongoing events of interest, we propose in this paper an approach inspired from the strategy used by fireflies to attract their prey. The Firefly Algorithm (FA) is a bio-inspired technique that was first developed by Yang [27]. This algorithm has been used to solve nonlinear optimization problems. It is based on observations from the social insect colonies, where each individual (for instance firefly glowing through bioluminescence) appears to operate for its own benefit and yet the group as a whole performs to be highly organized. The FA have been used in the literature for drone localization [28] and drone route planning [29]. In order to use this algorithm, we will assume that the drones form a network (IoD: Internet of Drones, or also the swarm) containing n drones (also fireflies). Each drone d has a set of dynamic collaboration options (also solutions) $\{x_{si} : i = 0, \ldots, m\}$ where each x_{si} is a neighbouring drone collaborator candidate with a fitness value $f(x_{si})$. Every drone has also a probability (also brightness) to attract collaborators that matches the brightness of the firefly it represents. Based on this probability, an attractiveness β_d is defined as the strength of the drone d in attracting other drones. This attractiveness is calculated as follows:

$$\beta_d = \beta_{d0}\, e^{-\gamma l^2} \tag{E1}$$

where β_{d0} is the attractiveness of the drone d at location $l_d = 0$, γ is the coefficient of brightness fading (corresponds to fireflies' light absorption coefficient), and r is the distance between the drone d and the drone being attracted.

3.2.1. Assessment

When a drone detects an event, it starts by assessing its type and its

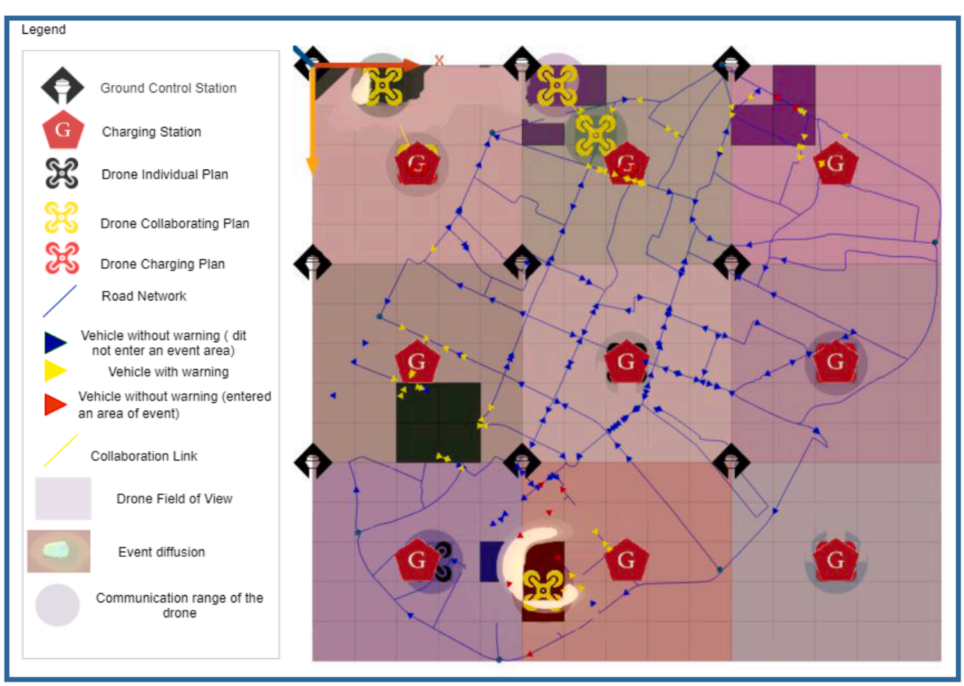

Fig. 4. Setup of our simulation area of interest.

scope (see Fig. 3). To do so, it analyzes the data it was able to collect as well as the information it holds about the geographic locations in and around its flying path. If the drone is not capable of managing the event on its own, it self-nominates as Mission Leader (ML). The ML has the role to coordinate the joint planning of paths to deal with the event. To this end, it will generate an Event Map as a matrix having the same size as the grid covering the spatial extent of the event (see Fig. 3). The idea of this map is to highlight the intensity of the event in each cell of the grid. To illustrate our idea, we reflect in the matrixes dEM and cEM below the examples of the discrete event and the continuous event appearing on Fig. 3, respectively. In dEM, we report the number of events per cell, whereas in cEM we report the percentage of the cell's area covered by the event.

$$dEM = \begin{pmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 2 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 2 & 1 & 0 & 0 & 3 \\ 1 & 1 & 1 & 0 & 0 & 0 \end{pmatrix} \quad cEM = \begin{pmatrix} 0.1 & 0.5 & 0.8 & 1.0 & 0.5 & 0.3 \\ 0.8 & 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 0.0 & 0.1 & 0.7 & 1.0 & 1.0 & 0.5 \\ 0.0 & 00 & 0.4 & 1.0 & 0.7 & 0.1 \\ 0.0 & 0.0 & 0.7 & 0.8 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.9 & 0.6 & 0.0 & 0.0 \end{pmatrix} \qquad \text{(M1)}$$

3.2.2. Setup

Once the geographic location of the event is delimited, the ML drone d creates a software agent (called Agent Mission Leader – AML) that will manage all the actions related to this event on its behalf. The AML will then notify the agent assigned to its geographic zone (called Agent Zone – AZ). The AZ will, in its turn, create specific agents for each cell of the zone where the event is detected (each agent is called Agent Cell – AC_i, for i = 0, …, n where n is the number of cells affected by the event). In order to motivate the mutual collaboration of drones, we propose to assign rewards for the management of events in the cells. More specifically, each AC_i will calculate in the setup phase the reward for the management of the event in its cell as follows (E2 and E3):

$$\rho_c = \alpha * \frac{\mathrm{Event}_{c,t}}{\mathrm{Surface}_c} * \rho_0 \qquad \text{(E2)}$$

$$\rho_0 = \mathrm{P}_{E,c} * \mathrm{I}_{E,c} \qquad \text{(E3)}$$

Where α is a factor that reflects the priority that an agent (i.e. a drone) will assign to a cell to visit it. In addition to varying depending on the ongoing event, the range of α could vary based on the mission of drones and their envisioned use. $\mathrm{Event}_{c,t}$ represents the surface of the cell c which is covered by the ongoing event at time t (it also represents the number of discrete events in the cell at t), $\mathrm{Surface}_c$ represents the total surface of the cell c, and ρ_0 represents the initial reward of the cell c. We calculate this reward as the probability of the event E to happen in the cell c times the expected impact of E on c. Without loss of generality, we assume that this impact is predefined by the application managers.

Once the rewards of all the cells are calculated, the AZ will compile the total reward for the whole zone as a sum of rewards (Equation E4) or as a matrix of rewards (Matrix M2). The sum of rewards is useful for any collaboration/competition aiming to manage events happening in different zones (in this case, the AZ agents will compete and collaborate to attract resources that would support the management of events happing in their zones. This collaboration/competition is out of the scope of this paper and will be the subject of an upcoming publication). The matrix of rewards is basically used by a ML drone to attract drone collaborators for the management of the events that it (i.e. the ML drone) detected in its zone. It can also be used during the competition between several ML drones to attract support for the management of events they detected in the same zone.

$$\rho_z = \sum_{i=0,j=0}^{i=n,j=m} \rho_{ci,j} \; where \; \rho_{ci,j} \text{ is the reward of the cell } i,j (i \le n \text{ and } j \le m) \qquad \text{(E4)}$$

$$\rho_z = \begin{pmatrix} \rho_{c0,0} & \rho_{c0,1} & \cdots & \cdots & \cdots & \rho_{c0,m} \\ \rho_{c1,0} & \rho_{c1,1} & \cdots & \cdots & \cdots & \rho_{c1,m} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \rho_{cn,0} & \rho_{cn,1} & \cdots & \cdots & \cdots & \rho_{c,n,m} \end{pmatrix} \qquad \text{(M2)}$$

Furthermore, the ML drone d will calculate its brightness β_d according to Equation E5.

$$\beta_d = \varphi_d * \frac{current_{battery}}{full_{battery}} \text{ where } \varphi_d \text{ is the reputation of the drone } d \qquad \text{(E5)}$$

In order to calculate the reputation of a given drone, which falls within the range [0,1], we propose to use the equation below (E6):

$$\varphi_d = \begin{cases} \varphi_0 \;, \; k = 0 \\ \left(1 - e^{-k}\right) * \dfrac{\mathrm{tot}_{\mathrm{positive}}}{\mathrm{tot}_{\mathrm{positive}} + \mathrm{tot}_{\mathrm{negative}}} + e^{-k} * \varphi_0, \; k > 0 \end{cases} \qquad \text{(E6)}$$

Where k is the total number of commitments that the drone d has made to deal with events. When k = 0, the drone has an initial reputation φ_0 (we assume in this paper that this reputation is the same for all drones). When k is different from 0, the reputation score is defined based on the cumulative values of the total positive commitments tot_positive (i.e. the cumulative rate of success of the drone during its k commitments) and the total negative commitments tot_negative. The role of the coefficients e^{-k} and $(1 - e^{-k})$ are used to reduce the amplitude of the initial oscillations in the reputation value φ_d when the value of k is low. This is also to prevent a single positive or negative commitment from either increasing or decreasing the reputation considerably. The more k grows, the less the effect of the initial reputation. In this case, the reputation of the drone will basically depend on its actions and performance

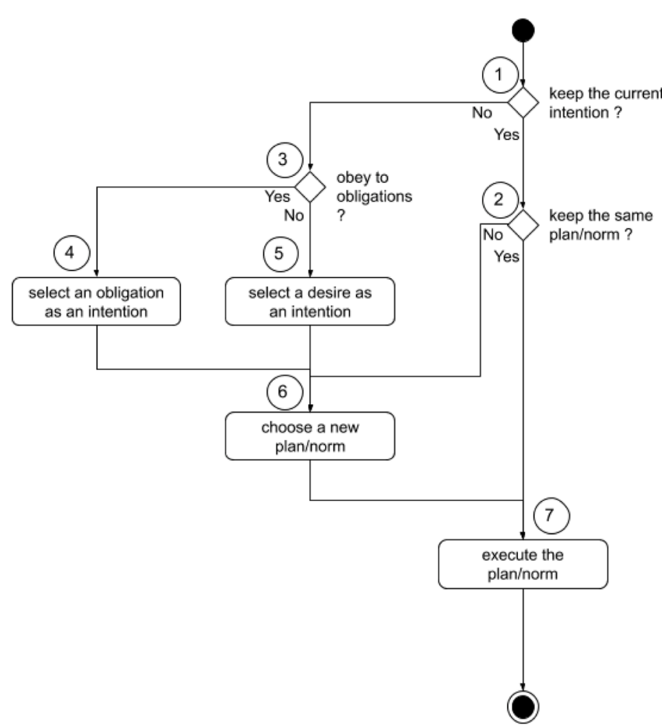

Fig. 5. Decision-making process of a Simple BDI GAMA agent [38].

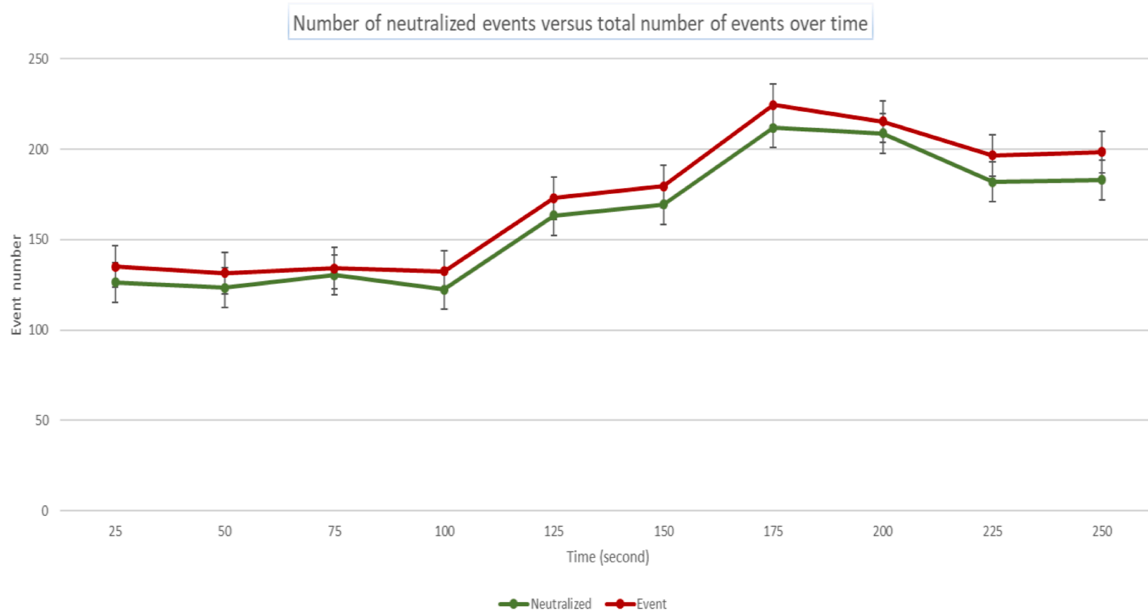

Fig. 6. Number of events neutralized with respect to the total number of events over time.

Along with the Reward Map and its brightness, the agent AML will broadcast its Capability Map where it will report its commitments to deal with the event in specific cells (these cells are selected by the agent AML based on the rewards it would receive from its actions). In addition to explicitly including all the information of the Event Map, the Capability Map will allow neighboring drones (i.e. the drones that will receive the request for collaboration from the agent AML) to select the cells they want to cover in a more informed way. Indeed, they will select the cells, which are closer to their flying paths and for which the ML drone did not commit to cover. In every cell of the Capability Map (dCap for a discrete event and cCap for a continuous event), the AML will indicate a vector (a, b, c) where a is the availability of the event in that cell (for discrete events $a = 0$ or 1 and for continuous events a is equal to the percent of area of the cell covered by the event). The parameter b indicates an estimate (in percent) of the capability of the drone to handle the event in that cell. To this end, the drone must check its schedule of actions, its current capabilities (mainly its remaining flight time), as well as the actions that it must execute. The drone must also evaluate a reward/cost function for a better decision-making (see Section 3.1.3). The parameter c will indicate if the drone is willing to handle the event in that cell ($c = 1$) or not ($c = 0$). An example of dCap (Matrix M3) and cCap (Matrix M4) are given below for the configuration depicted in Fig. 3:

$$dCap = \begin{pmatrix} 0 & 0 & 0 & 0 & (1, 1.0, 1) & 0 \\ 0 & (1, 0.5, 0) & 0 & 0 & 0 & (1, 0.8, 1) \\ 0 & 0 & (2, 0.2, 0) & 0 & 0 & (1, 0.5, 1) \\ 0 & 0 & 0 & 0 & 0 & 0 \\ (2, 0.1, 0) & (2, 0.0, 0) & (1, 0.3, 0) & 0 & 0 & (3, 0.3, 0) \\ (1, 0.0, 0) & (1, 0.2, 0) & (1, 0.0, 0) & 0 & 0 & 0 \end{pmatrix} \tag{M3}$$

$$cCap = \begin{pmatrix} (0.1, 0.3, 0) & (0.5, 0.5, 0) & (0.8, 0.7, 1) & (1.0, 0.9, 1) & (0.5, 0.7, 1) & (0.3, 0.6, 0) \\ (0.8, 0.2, 0) & (1.0, 0.6, 0) & (1.0, 0.5, 0) & (1.0, 0.5, 1) & (1.0, 0.7, 1) & (1.0, 0.6, 0) \\ 0.0 & (0.1, 0.9, 0) & (0.7, 0.5, 0) & (1.0, 0.6, 0) & (1.0, 0.7, 0) & (0.5, 0.5, 0) \\ 0.0 & 00 & (0.4, 0.4, 0) & (1.0, 0.6, 0) & (0.7, 0.7, 0) & (0.1, 0.5, 0) \\ 0.0 & 0.0 & (0.7, 0.5, 0) & (0.8, 0.5, 0) & 0.0 & 0.0 \\ 0.0 & 0.0 & (0.9, 0.1, 0) & (0.6, 0.0, 0) & 0.0 & 0.0 \end{pmatrix} \tag{M4}$$

3.2.3. *Bidding*

Drones that receive the message from the AML agent may either be interested to join the collaboration or not. Their decisions will be based on several parameters, including their current schedules, situations, and cost/benefit analysis of the collaboration. More precisely: (1) drones currently charging their batteries or busy will other commitments will ignore calls for collaboration; (2) drones with low energy levels do not commit to contribute to any collaboration unless nearby charging stations are available; and (3) drones in idle situations and receiving multiple calls for collaboration will select the best options based on their cost/benefit analysis. Drones that are interested in the call for collaboration will start by calculating the attractiveness they underwent from

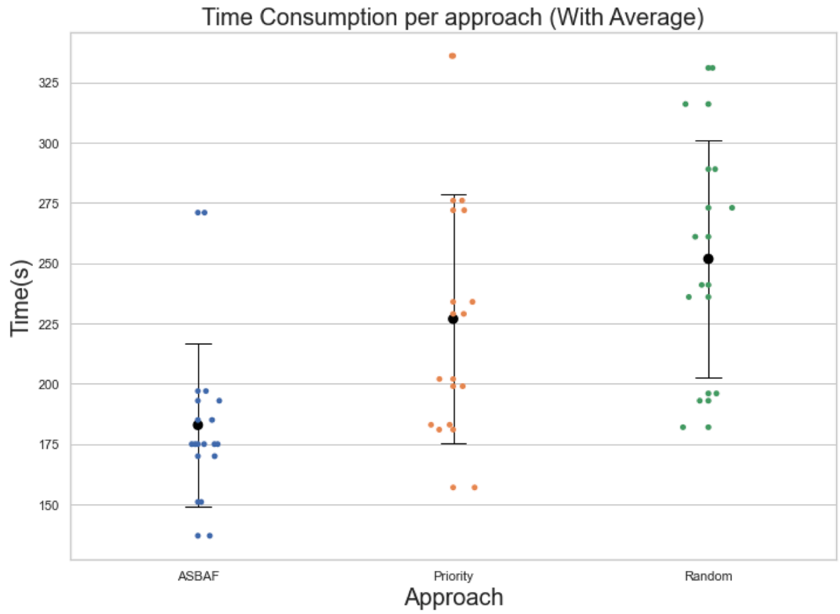

Fig. 7. Comparison of the three approaches in terms of processing time.

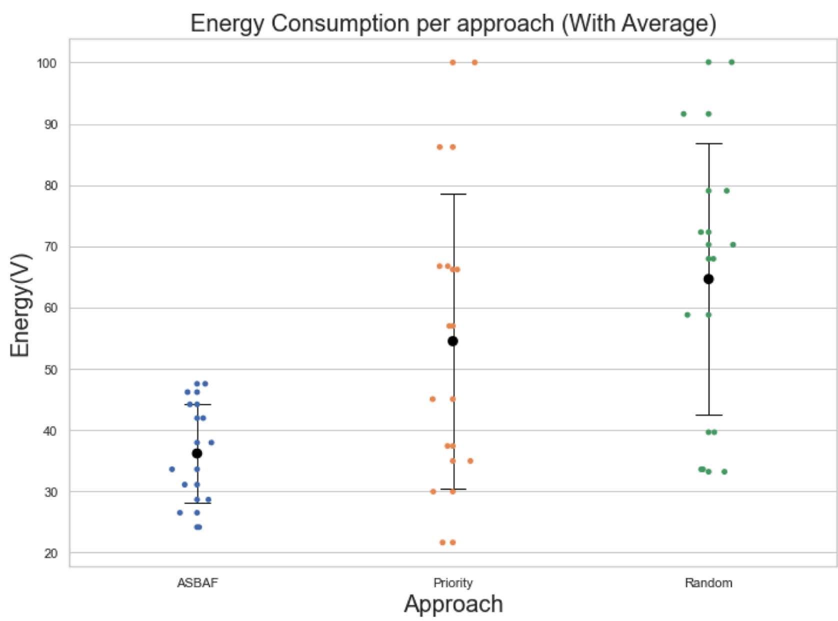

Fig. 8. Comparison of the three approaches in terms of energy consumptionAs we are particularly interested at proposing a solution for drone collaboration that is capable of increasing the benefits from drones' actions, we depict in Fig. 9and Fig. 10 the performance of the three approaches in terms of average rewards obtained by the drones with respect to processing time and energy consumption, respectively.

the ML drone in any cell of interest based on their own parameters using a bio-inspired Fire-Fly approach. In the following Equation (E7), we calculate the attractiveness $\beta_{d\to u}$ of a drone d to a drone u in a cell c:

$$\beta_{d\to u} = \beta_d \, e^{-\gamma l_c^2} \tag{E7}$$

where l_c is the distance between the drone u and the cell c and β_d is calculated as per the Equation E5.

The drone u will also calculate the cost and the benefit of its collaboration with the ML drone by managing the event in the cell c. To this end, we will consider in this paper the cost as the energy to be spent by the drone to cover c. According to [30], each drone consumes the following energy:

$$C_c(t) = (\lambda + \alpha k)t + P_{max}\left(\frac{k}{s}\right) \tag{E8}$$

where λ is the minimum power needed to hover just over the ground (when altitude is almost zero) and α is a motor speed multiplier. Both λ and α depend on the drone weight and the motor/propeller characteristics. P_{max} is the maximum power of the motor, s is the speed, and t is the operation time (i.e. the time interval during which the drone will be flying over the cell). The more the drone spends time to manage the event in the cell, the higher is its energy consumed. αk denote the relation between power and weight. The term $P_{max}(k/s)$ refers to the power consumption needed to lift to height k with speed s.

Furthermore, the benefit of managing the event in cell c at the time

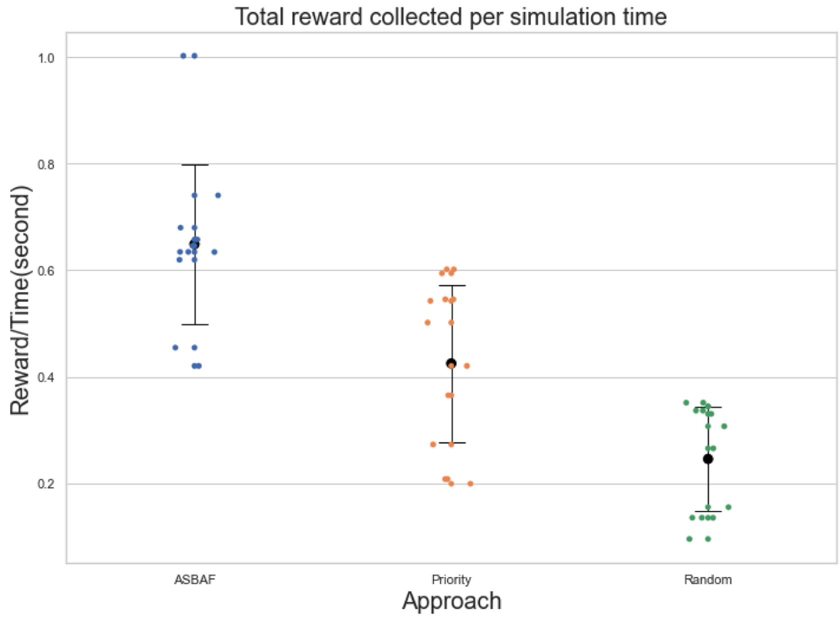

Fig. 9. Comparison of the three approaches in terms of reward with respect to processing time.

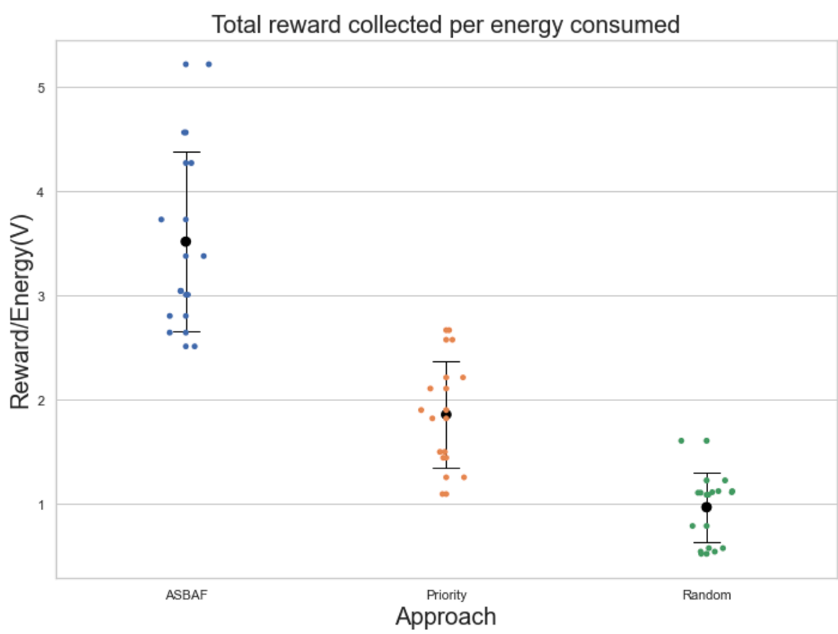

Fig. 10. Comparison of the three approaches in terms of reward with respect to energy consumption.

interval t is $B_c(t)$:

$$B_c(t) = \rho_c + \frac{1 - e^{-q(t)}}{1 + e^{-q(t)}} \tag{E9}$$

Where $q(t)$ is the number of charging stations available during t in the cell c (charging stations are used here to minimize the impact of energy constraints on the collaboration decision of the drone). ρ_c denote the reward of the cell as calculated in E2.

The goal of the drone u will ultimately be to optimize its cost-benefit analysis by handling events in several cells. The cost-benefit value CB_u is then calculated as follows (E10):

$$CB_u = \sum_{c=1}^{p} \frac{B_c(t) - C_c(t)}{(1 + r_c(t))^t} \tag{E10}$$

Where $B_c(t)$ is the benefit of the drone u when handling the event in cell c during the time interval t, $C_c(t)$ is the cost of the drone u when handling the event in cell c during the time interval t, $r_c(t)$ is the additional cost rate (or also the depreciation rate of acting during t) when handling the event in cell c during the time interval t, and p is the number of cells in which the drone u is interested to help (i.e. to collaborate).

The decision of the drone u to participate in the collaboration will then be (E11):

$$Collaboration_{u\to d} = \beta_{d\to u} * CB_u \tag{E11}$$

Once all the calculations are done, the drone u (which is interested to collaborate with the ML drone) will create a mobile agent that will migrate where the negotiation will happen as instructed by the ML drone (see the Virtual environment in Fig. 2). The agent will be bidding and

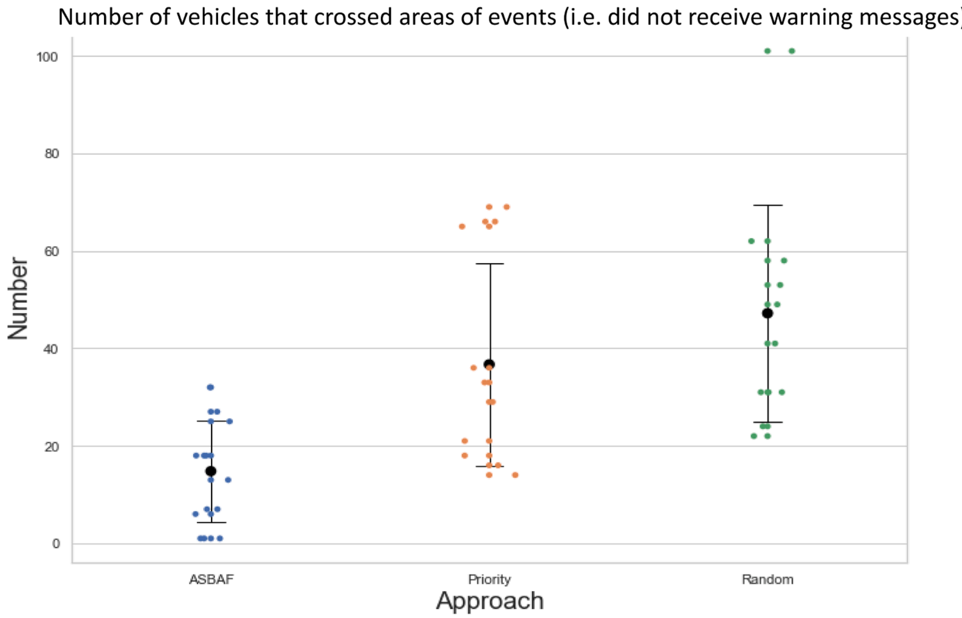

Fig. 11. Numbers of vehicle entering event areas without receiving any warnings.

negotiating on behalf of the drone u with the agents representing the other drones, which are interested in the collaboration. To this end, it will use a Bidding Map (see M5), wherein the drone u reports in every cell a vector $\langle x, y\rangle$ with x indicating how much (in percent) u is estimating itself able to handle the event in the corresponding cell. The parameter y will indicate if the drone u is willing to carry out the necessary actions in that cell ($y = 1$) or not ($y = 0$). In the Bidding Map, a vector $\langle 0, 0\rangle$ is reported in the cells that the drone is not interested to cover. The following matrix (M5) represents an example of what a Bidding Map may look like for a continuous event. The bids of the collaborating drones will be conveyed to the AML agent for a first screening of a joint action plan (i.e. identifying the cells where only one bid was received, cells where multiple bids are received, etc.).

$$\mathrm{Bid}_u = \begin{pmatrix} \langle 0,0\rangle & \langle 0.7,1\rangle & \dots & \dots & \dots & \langle 0.6,0\rangle \\ \langle 0.5,0\rangle & \langle 0.9,1\rangle & \dots & \dots & \dots & \langle 0,0\rangle \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \langle 0,0\rangle & \langle 0,0\rangle & \dots & \dots & \dots & \langle 1.0,1\rangle \end{pmatrix} \quad \text{(M5)}$$

3.2.4. Agreement

In order to effectively manage the ongoing event, the agents representing the different drones (i.e. the ML drone as well as the bidding drones) will be negotiating the joint action plan. More specifically, upon reception of the bids, the AML agent will operate according to the following three cases:

- A cell is requested by one and only one bid – The bidding drone will be assigned to the management of the event in that cell.
- A cell is requested by several bids – The bidding agents will negotiate to choose who will take care of the event in the cell. To this end, they will follow the negotiation approach proposed in [31].The bidding agents can also jointly collaborate in handling the event in the same cell (this is particularly needed when they are dealing with discrete events like intruders. In this case, every drone could, for example, track one intruder). The reward, in this case, will be shared between the participating drones. Agents may also negotiate the durations of their commitments (e.g., full commitment, 50% commitment from mission starting, 20% commitment after mission starting, etc.) and the types of their commitments (e.g., without revoke, with revoke, etc.). Agents will then agree on how to share the rewards. The AML will always work on preparing backup options in case a collaboration team member revokes its commitment. Intensive research works are already available on multi-agent system negotiation. Proposing a new related approach is, therefore, out of the scope of this paper.
- A cell is not requested by any bid – The bidding agents will negotiate a plan to cover this cell. For instance, some drones may deliberately select to not cover some cells, in spite of their capabilities to manage the ongoing events in satisfactory ways. Their decisions may be based on their cost-benefit analysis. Since events are by nature dynamic, their effects on cells as well as the rewards related to their management would change. In other words, the situation would evolve into one of the two cases above. New agreements will, then, be negotiated based on the new facts as explained above.

3.2.5. Feedback

In this step, drones will report to their agents the status of the events within their sensing ranges (while focusing on the cells they are currently covering), their current performance, as well as their current capabilities. On the collaboration remote site, the delegated agents will compile the data received from their drones and identify whether new plans need to be generated. Meanwhile, the AML agent will compile and examine the drone reports. It will also generate and share a new map of the event. Based on this map, all the agents will rebuild their capability maps and negotiate accordingly. Based on the new data, agents may decide to exchange or revoke commitments, change flight trajectories, reschedule their charging plans, etc.

Furthermore, during the feedback step, drones will identify the vehicles on the road network that may be affected by the ongoing events. Based on the intensities and the impact of these events, drones will issue the right warnings to these vehicles. We assume in our approach that once a warning message is received, the vehicle should stop. In other words, planning alternative routes for the vehicle is out of the focus of this paper. The number of vehicles that a given drone will successfully prevent from incurring any damage or any significant delays on their commutes due to the events could be translated into a reward. This issue is not within the scope of this paper.

4. Implementation and results

4.1. Implementation

In order to demonstrate the performance of our approach, we consider in this paper the specific scenario of wildfire management where fire could appear sporadically in space and time and disrupt the traffic flow accordingly. Several agent-based simulation frameworks are currently available, including JADE, JADEX, JACK, JASON, GAMA, JANUS, JASIM, and EMERALD. Based on the survey presented in [32], we selected GAMA to run our simulations on an area of interest of size 6.51 km * 5.14 km. As agent interaction protocol, we used FIPA ACL communication for its proven successful use in a variety of research works based on software agents [33, 34].We divided this area into 9 zones, each of which of size 2.17 km * 1.71 km Figure 4. We also divided every zone into 5 cells (25 cells in each zone), each of which of size 434.4 m * 342.8 m. For the sake of simplicity, we used one ground station and one static charging station in every zone. We also used 9 drones, each of them has a square field of view like in [35] of 148.42m^2 and a maximum flight duration of 400 cycle (cycle=1 second). More information are available in Table 2 where we summarize the specific features of our simulations.

We designed our agents according to a Belief-Desire-Intention (BDI) architecture. This architecture enables, indeed, a straightforward formalisation of human reasoning with easy to understand intuitive concepts [36]. It also enables the implementation of realistic decision-making processes that support social norms as well as uncertainties of perceptions in the application environment [37]. Within this setup, every agent has a set of predicates and beliefs to model the current external state of the environment as well as the current internal state of the drone. Based on these beliefs, a set of rules are used to identify the actions that an agent (ultimately a drone) can execute as well as select the actions (also intentions) that should be executed based on the current situation. A set of plans is then used to define the agent behavior based on its intentions. For the purpose of implementation, we used in this paper the built-in BDI architecture of GAMA, which is known as Behavior with Emotions and Norms – BEN [38] (see Fig. 5). On the issue of data exchange, the agents interact using the well-known Agent Communication Language (ACL). We run our simulations ten times and recorded their related performance in terms of execution time, energy consumption, and total rewards obtained by the collaborating drones. For a better assessment of this performance, we also compared the results of the proposed ASBAF approach with an approach where agents plan their paths by randomly selecting one of non-covered cells each time as well as with an approach where agents plan their paths by selecting the next cells to cover based on their priorities (similar to the approach proposed in [16]). We call these approaches in what follows ASBAF, Random, and Priority-Based.

4.2. Performance evaluation

We depict in Fig. 6 the number of events that appeared sporadically during different time slots (represented with red color) as well as the number of events that were neutralized by our ASBAF approach (represented with green color) during the same time slots. The events that were not neutralized (represented by the gap between both lines) will be added to the events that are generated in the next time slot. We can clearly see that in all our simulations, the gap between both numbers of events is limited. In other words, our approach is capable of neutralizing most of the events. As new events continue to be created by our simulations randomly and/or some ongoing events continue to evolve, the gap does not necessarily close (i.e. some events have not been neutralized).

Furthermore, as we can see in Fig. 7 and 9, ASBAF generally outperforms the two other approaches (i.e. Random and Priority-Based) in terms of average processing time during the 10 simulations that we run. In some cases, our approach is taking more time to neutralize the ongoing events compared to the other approaches. This is basically happening due to the sporadic distribution of the events that may require additional negotiation time between the agents before they start their actual actions. Furthermore, it may happen that the Random approach could require high processing times as drones may select to deal with the same event at the same time while ignoring other important events that would become more severe over time. The processing time may also increase when the events selected for the next moves are far from the current locations of drones (i.e. drones will keep moving between far way locations). The same situation may also happen in the context of the Priority-Based approach, which would result into high processing time. The same explanations could be given about the performance of the three approaches in terms of average energy consumption (Fig. 8 and 10). Indeed, while our approach ASBAF may consume additional energy for negotiation needs, the Random approach and the Priority-Based approach may consume additional energy due to unnecessary travels between events' locations.

Furthermore, in order to assess the effect of our collaboration approach on the safety of vehicles, we counted the number of cars that have entered areas affected by ongoing events (i.e. the number of cars that did not receive any warning message from drones). More specifically, we run 10 simulations for each approach and reported on Fig. 11 the average number of vehicles that have crossed event areas. Our results are showing that the performance of our ASBAF approach is better than the Priority and Radom approaches.

5. Conclusion

We addressed in this paper the important issue of drone collaboration planning. We proposed a five-step approach that relies on the interactions of software agents to jointly decide on a common plan for the management of ongoing events. This plan results from a collaborative setup and execution of individual drone plans. Its creation is driven by a bio-inspired Firefly algorithm that issues attraction forces reflecting the intensities and impact of ongoing events. It is also driven by an agent competition solution that uses rewarding mechanisms as well as a cost-benefit analysis to identify the right drone tasks to execute at the right time. The proposed solution is also capable of issuing appropriate warnings to vehicles to prevent them from incurring the impact of ongoing events. Our simulations showed promised results in terms of processing time, energy consumption, and total rewards obtained from the drones' actions, particularly in comparison with two other planning approaches relaying on random and priority-based selection of the next locations that drones will visit respectively. In addition to improving our vehicle warning mechanisms, our future works will focus on implementing the collaboration between neighboring zones. It will also focus on investigating the impact of mobile charging stations on the drones' collaboration decisions and assessing the resulting performance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Dr. Nafaâ Jabeur is Associate Professor and Director of Research at the German University of Technology in Oman (GUtech). He received his PhD and MSc degrees in Computer Science from Laval University, Quebec, Canada in 2006 and 2001, respectively. He has over than seventeen years of experience in the industrial and academic sectors. Nafaâ has participated in several R&D projects, edited 2 books, and authored more than 80 research papers in prestigious conferences and high ranked journals. His-main research interests include Smart cities, Transportation, Blockchain, Drones, and Artificial Intelligence.